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Memristor-Based Affective Associative Memory Neural Network Circuit with Emotional Gradual Processes

Meiling Liao [1] · Chunhua Wang [1,✉] · Yichuang Sun [2] · Hairong Lin [1] Cong Xu [1]

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Abstract In the existing affective associative memory neural network circuits, the change of emotions in the affective associative learning and forgetting processes is abrupt and the intensity of emotions is invariable. In fact, the transition from one emotion to another is a gradual process. In this paper, to realize the progressive changes of emotional intensity in the affective associative memory neural network, the gradual learning, gradual forgetting and gradual transferring processes of emotions are proposed and the memristor-based circuit of the affective associative memory neural network is designed. In the designed circuit, the firing frequency of output neurons is closely correlated with the intensity of emotions. The higher the firing frequency of output neurons, the stronger the emotional intensity. Based on the associative memory rule, the dynamical change of the synaptic weights leads to the gradual variation of the frequencies of output neurons. Thus, the function of variable emotional intensity can be realized and the gradual processes can be achieved. The PSPICE simulation results are given to verify that the proposed circuit could realize the affective learning, forgetting and transferring functions with gradual processes.

Keywords Memristive neural network, circuit simulation, associative memory, affective model, conditioning reflex

1 Introduction

Artificial neural networks (ANNs) have always been a hot topic in the field of artificial intelligence. They abstract the neurons of the human brain from the perspective of information processing and form different networks according to the different connection methods. In recent years, utilizing artificial neural networks to imitate biological behaviors and their means of information processing has attracted the attention of scholars. For example, there is a lot research realized learning, memory and calculation based on the rules of biological associative memory, non-associative learning, and affective computing [1–11]. Currently, the calculation and processing of artificial neural networks are mainly carried out by software, which consumes a lot of time for operating serially. The parallel processing mode of hardware is compatible with the distributed processing method of biological neural network, which greatly improves operating speed [12]. The hardware implementation of neural networks is mainly based on transistor devices traditionally, which is limited by the size and functions of transistors. As a result, the synapse density of artificial neural networks implemented by transistors is much lower than that of biological neural networks. Since the memristor was predicted by Chua [13] and first produced by Strukov *et al.* [14], it has attracted widespread attention. Because of its nanometer-scale size and resistive characteristics, memristor has become a suitable candidate for building large-scale artificial neural networks with bionic synapses. Recently, memristive neural networks have been widely studied in theory and application. The theoretical research mainly focuses on dynamics, such as stability [15–20], synchronization [21–23], aiming to discover new functions and new phenomena of the memristive neural networks. Meanwhile, memristive neural networks have made breakthroughs in many

✉ Chunhua Wang
E-mail: wch1227164@hnu.edu.cn
[1] Meiling Liao, Chunhua Wang, Hairong Lin and Cong Xu are with the College of Information Science and Engineering, Hunan University, Changsha, 410082, China (email:liao0526@hnu.edu.cn;wch1227164@hnu.edu.cn;haironglin@hnu.edu.cn;xucong0703@163.com)
[2] Yichuang Sun is with the School of Engineering and Computer Science, University of Hertfordshire, Hatfield AL109AB, U.K.(email:y.sun@herts.ac.uk)

application fields such as image processing [24–26], pattern recognition [27–30], intelligent control [31,32] to mimic the biological nervous systems for information processing and calculation.

The Pavlov's associative memory theory refers to multiple associations between one stimulus and another unconditioned stimulus with reward or punishment, so that individuals can learn to trigger a conditioned response similar to the unconditioned response when presented with that stimulus alone. That theory is the basis to realize affective associative learning and forgetting [33–35]. However, the emotional system of humans is quite complex, how to simulate the transfer process of human emotions is meaningful [36–38]. In the field of classical conditioning, "The Case of Peter" is an experiment that shows the transfer process of affective associative memory [35]. In that experiment, food is an unconditional stimulus that will cause the pleasure feeling of Peter, while the rabbit is a conditional stimulus that will cause the fear feeling of Peter. However, when the conditional stimulus (the rabbit) was given combined with the unconditional stimulus (food) many times, the fear feeling became weaker gradually while the pleasure feeling became stronger gradually, which means one kind of emotional associative memory transferred to another kind of emotional associative memory gradually. That is the gradual transferring process, which includes the process of gradual learning and the process of gradual forgetting of emotions.

So far, a few studies have focused on the circuit design of affective associative memory neural network. In [39], the associative memory neural network was first proposed to model human emotions in social relations, but the model lacks the necessary circuits of neurons that conform to the characteristics of biological neurons. Wang *et al.* proposed a full-function emotion model based on the associative memory neural network to simulate the learning and forgetting processes of emotions [40]. And in [41], authors designed the rule of affective multi-associative learning, which discussed the learning and forgetting of multiple emotions. However, the intensity of emotions is invariable and the processes of gradual learning and gradual forgetting are not considered in [39–41]. Actually, the change of emotions in the affective associative learning and forgetting processes is not abrupt but gradual. In addition, the gradual transferring process from one kind of emotional associative memory to another is not contained in these emotion models. Considering the coherent changes of affective associative memory, it is necessary to implement the gradual processes to better simulate the learning, forgetting and transferring stages of emotions.

Therefore, concerned with the issues mentioned above, this paper proposes the circuit design of affective associative memory neural network with gradual processes, which includes the gradual learning, gradual forgetting and gradual transferring stages of emotions. In the designed circuit, neurons with variable firing frequency and memristor-based synapses constitute the basic framework of the neural network. The firing frequency of output neurons is closely correlated with the intensity of emotions. Moreover, the dynamic adjustment of synaptic weights will lead to the change of firing frequency of output neurons, which will result in the changes of emotional intensity. Combined with the associative memory rules, the emotional intensity gradually increases or decreases in the learning, forgetting and transferring stages. Thus, the gradual learning, gradual forgetting and gradual transferring processes are realized. In those stages, as the degree of associative memory deepens (or weakens) gradually, the intensity of certain emotions will gradually become stronger (or weaker), which looks like a coherent change in emotions. That's why these stages are called 'gradual' processes.

The rest of this paper is arranged as follows. Section 2 describes the emotional gradual transfer phenomenon from an experiment in the classical conditioning field. Section 3 presents the diagram of the affective associative memory neural network model. In Section 4, the basic components that make up the circuit of the affective associative memory neural network are introduced. Then, the circuit design of the emotional gradual transferring process is presented in Section 5. Section 6 realizes and analyzes the whole circuit design of the affective associative memory network with gradual learning, gradual transferring and gradual forgetting processes.

2 A Case of Emotional Gradual Transferring Phenomenon

The rule of emotional gradual transferring is derived from "The Case of Peter" which is elaborated in Behaviorism written by John B. Waston [35]. "The Case of Peter" is an experiment to reconstruct affective associative learning to eliminate fear responses. The process and rules of the experiment are described as follows.

Peter is a three-year-old child. In the beginning, he was afraid of rabbits. Peter showed fear by crying when a rabbit was in his sight, which is a previously-established conditioned response before the experiment. Candy is another unconditional stimulus. Peter showed pleasure when researchers offered him candy, which is an unconditioned response. It should be noted that candy is not an unconditional stimulus of fear feeling and the rabbit is not a conditioned stimulus of pleasure feeling. Specifically, Peter showed no fear when researchers offered him candy and showed no pleasure when the rabbit occurred to his sight. Afterwards, despite researchers offering Peter candy, he still showed fear when the rabbit was in his sight at first.

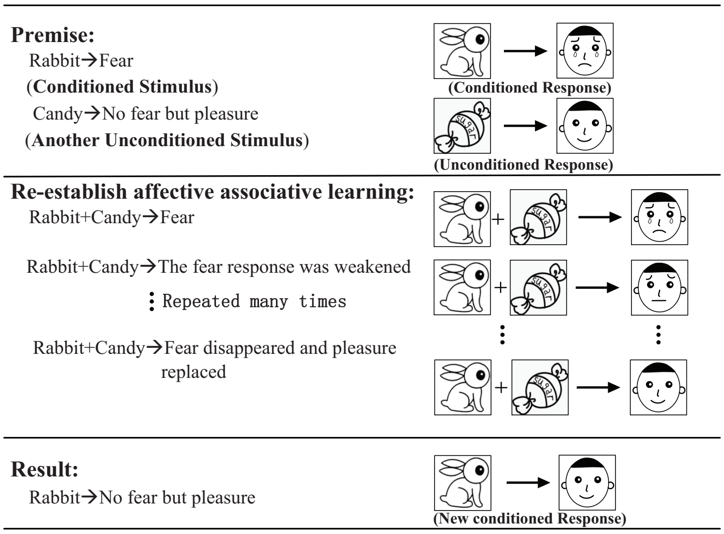

Fig. 1: The diagram of "The Case of Peter" experiment.

After several such simultaneous pairings of the two stimuli (candy and rabbit), the fear response of Peter gradually became weak and Peter showed tolerance. As the simultaneous pairings process repeated, the degree of tolerance of Peter was getting higher. Finally, the fear response of Peter disappeared and he could even play with the rabbit agreeably, which means the process of re-establishing affective associative learning was completed and the fear emotion transferred to pleasure emotion. When the rabbit came to Peter's sight again, the pleasure feeling of Peter replaced the fear feeling, which means Peter conquered fear. The experimental framework of "The Case of Peter" is shown in Fig. 1.

In the process of the re-establishing affective associative learning, the pleasure feeling was strengthened gradually while the fear feeling was weakened gradually by repeating the pairings of the two stimuli (candy and rabbit). In fact, the aforesaid re-establish affective association learning can be explained as the process of learning one emotion and forgetting another emotion. In this learning and forgetting process, the transition from one emotional state to another should not be abrupt but gradual. The emotional intensity will change in the gradual transferring process, this is the gradual transfer phenomenon of emotions.

3 The Diagram of the Affective Associative Memory Neural Network Model

Based on "The Case of Peter" experiment, the diagram of associative memory neural network for modeling emotions is shown in Fig. 2.

As shown in Fig. 2(a), "C" and "R" represent the "candy" signal and the "rabbit" signal, respectively. N_1 denotes the input neuron that receives the "candy" signal. N_2 denotes the neuron that receives the "rabbit" signal. N_3 and N_4 are output neurons which generate the emotional signal "pleasure" and "fear" respectively. The synapses that constructed by memristors connect the input neurons and output neurons. w_{01}, w_{02}, w_{13}, w_{14}, w_{23} and w_{24} denote the synaptic weights. The output signals of N_3 and N_4 are

$$\begin{aligned} Out(N_3) = f(&f(C * w_{01} - \theta_1) * w_{13} + \\ &f(R * w_{02} - \theta_2) * w_{23} - \theta_3) \end{aligned} \tag{1}$$

$$\begin{aligned} Out(N_4) = f(&f(C * w_{01} - \theta_1) * w_{14} + \\ &f(R * w_{02} - \theta_2) * w_{24} - \theta_4) \end{aligned} \tag{2}$$

where θ_1-θ_4 represent the threshold terms of neurons N_1-N_4. $Out(N_3)$ and $Out(N_4)$ represent the emotional intensity of pleasure and fear emotions respectively. $f(\cdot)$ is the activation function defined as

$$f(x) = \begin{cases} g(w) & x \geq 0 \\ 0 & x < 0 \end{cases} \quad (g(w) \neq 0, g(w) \propto w) \tag{3}$$

It should be noticed that $g(w)$ is a nonlinear function positively related to weights, and $g(w)$ will increase (decrease) as the corresponding synaptic weights increase (decrease). In this paper, the synaptic weights w_{01} and w_{02} are set equal to 1, and the threshold terms θ_1 and θ_2 are set equal to 0. Because the candy signal

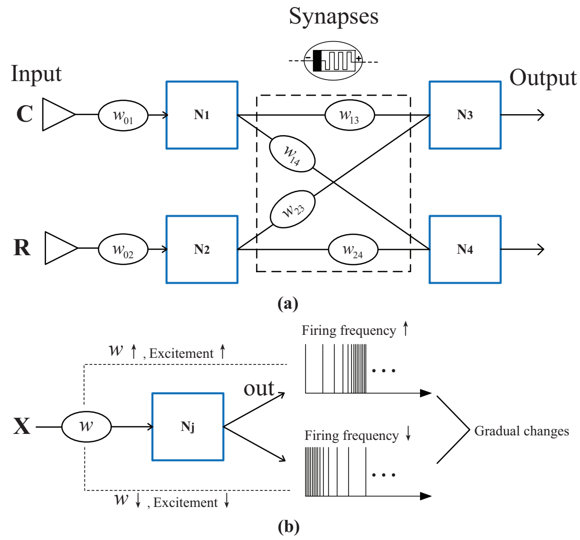

Fig. 2: The affective associative memory neural network model based on "The Case of Peter" experiment. (a) The whole neural network computing framework. (b) Single neuron computing framework.

will always cause the pleasure emotion and not cause the fear emotion, the weight w_{13} is set approximately equal to 1 while w_{14} is set approximately equal to 0. At the beginning, the rabbit signal causes the fear emotion of Peter, so the synaptic weight w_{24} is set approximately equal to 1, while w_{23} is set approximately equal to 0. When the input signal C and R appear simultaneously, the synaptic weight w_{24} will decrease while w_{23} will increase. As a result, the output $Out(N_4)$ decreases while $Out(N_3)$ increases, which means that the associative memory between "rabbit" and "fear" gradually transfers to the associative memory between "rabbit"and "pleasure". This is the gradual transferring process of emotions. In the learning process, an increase in synaptic weight w_{23} will result in the increases of $Out(N_3)$. In the forgetting process, an decrease in synaptic weight w_{24} will result in the decreases of $Out(N_4)$.

Fig. 2(b) shows the single neuron computing framework. X represents the input signal of the neuron N_j. The output signal $Out(N_j) = f(X * w - \theta_j)$. When X occurs and $X * w > \theta_j$, the neuron N_j will be activated to firing. Afterwards, the increases (decreases) in the synaptic weight w will result in the excitement of neuron N_j to increase (decrease). Then, the firing frequency of N_j will increase (decrease). If w does not change, $g(w)$ and $Out(N_j)$ will maintain as a constant, and the firing frequency will not change. Thus, the increases (decreases) of $Out(N_j)$ will be manifested by the increases (decreases) in firing frequency of the neuron N_j. Moreover, the firing frequency of output neurons is correlated with the intensity of emotions. Specifically, the higher the firing frequency of output neurons, the stronger the emotional intensity. The dynamical change of the synaptic weights leads to the gradual variation of the frequency of output neurons, then the intensity of emotions gradual changes in the learning, forgetting and transferring stages. Therefore, the affective associative memory neural network with emotional gradual processes could be achieved.

4 Circuit Components in Affective Associative Memory Neural Network

4.1 Memristor Model

In memristive neural network, memristors are key components to simulate synaptic functions. At present, various memristor models with different materials have appeared one after another. Meanwhile, the corresponding mathematical models of the memristors have also been proposed. For example, HP Labs [14] first proposed the TiO_2 memristor model but it does not contain the characteristics of voltage threshold or current threshold. The paper [42] proposed a flexible TEAM memristor mathematical model, which includes the characteristics of current threshold and state variable dependence. But voltage control models of the memristors are often needed in practical applications. In [43], the authors proposed an extended VTEAM voltage control model based on the TEAM model. Nevertheless, due to the fixed change rate of the state variables, this model is difficult to describe the principles of synaptic strength change. The memristor model with voltage thresholds used in this paper is proposed in [44], which is named memristor synapse model and based on the experimental data of the AIST memristor [29]. The mathematical model is expressed as

Table 1: Parameter settings of memristor

Parameters	Setting
$R_{on}(\Omega)$	10
$R_{off}(\Omega)$	1000
$V_{T-}(V)$	-4.1
$V_{T+}(V)$	4.1
$D(nm)$	3
$\mu_v(m^2s^{-1}\Omega^{-1})$	3×10^{-8}
$i_{on}(A)$	0.025
$i_{off}(A)$	0.02
$i_0(A)$	1×10^{-5}

follows.

$$\frac{dw(t)}{dt} = \begin{cases} \mu_v \frac{R_{on}}{D} \frac{i_{off}}{i(t) - i_0} f(w(t)) & v(t) > V_{T+} > 0 \\ 0 & V_{T-} \leq v(t) \leq V_{T+} \\ \mu_v \frac{R_{on}}{D} \frac{i_t}{i_{on}} f(w(t)) & v(t) < V_{T-} < 0 \end{cases} \tag{4}$$

$$f(w(t)) = 1 - (\frac{2w(t)}{D} - 1)^{2p} \tag{5}$$

Where $w(t)$ and D denote the width of doped region and thickness of memristive device respectively, i_0, i_{off} and i_{on} are currents fixed with constant values, $v(t)$ is the voltage applied across the memristor, V_{T+} and V_{T-} are threshold voltages. R_{on} is a low memristance, which represents the memristor is completely doped. R_{off} represents a high memristance when the memristor is completely undoped. $f(w(t))$ is a window function with an adjustable parameter p.

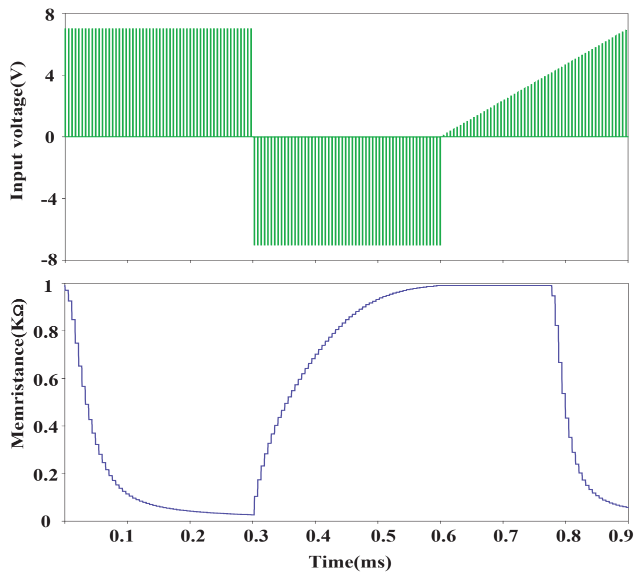

Fig. 3: PSPICE simulation results of memristor.

The parameter settings of the memristor in this paper are shown in Table 1. The voltage thresholds V_{T+} and V_{T-} are set to $4.1V$ and $-4.1V$, respectively. Only when the input voltage of memristor is greater than V_{T+} or less than V_{T-}, the memristance will change. Fig. 3 shows the change of the memristor under the effect of the input voltage. When positive voltage pulses greater than V_{T+} are applied to the positive terminal of the memristor, the memristance first decreases at fast speed, and then approaches the minimum at gentle speed. Similarly, the memristance will increase when negative voltage pulses less than V_{T-} are applied to the negative terminal of the memristor.

4.2 Neuron Model

Neurons are the most basic structure and function unit of biological nervous system, which equip the ability to transmit bioelectric signals. The leaky integrate-and-fire neuron is an effective model with discharge process similar to biological neurons [45]. In Fig. 4, the leaky integrate-and-fire neuron model is presented and the differential monostable trigger is added. The frequency of output pulses of this neuron model will be adjusted by the amplitude of the input current. Moreover, the width of output pulses can be adjusted by setting the parameters of the differential monostable trigger. The firing principles of this neuron are presented as follows.

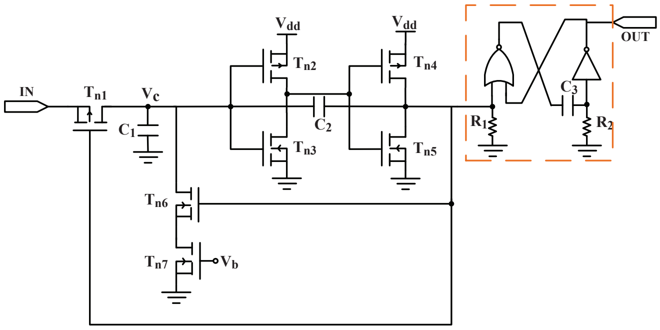

Fig. 4: Circuit of the neuron model.

The input terminal IN acts as a signal receiver to receive the input signal or the output signal from the pre-neuron. The neuron is at an inactive state when there are no input signals. C_1 and C_2 are membrane capacitors, which will integrate the input current. As the input current flows in, the voltage V_c will increase. When the voltage V_c reaches the threshold V_{th} of the inverter composed by the transistors T_{n2} and T_{n3}, the neuron will be activated and output a high level pulse. At that time, the input signal is blocked and the neuron experiences the refractory period while the transistor T_{n6} is turned on and T_{n1} is turned off. Meanwhile, capacitors C_1, C_2 are discharging through the transistors T_{n6} and T_{n7} and the voltage V_c gradually decreases. When V_c drops below the threshold of the inverter, there is no output pulse and the transistor T_{n6} is turned off and T_{n1} is turned on, the neuron is restored to the inactive state and will ready to meet the next input signal. The PSPICE simulation result of the neuron model is shown in Fig. 5.

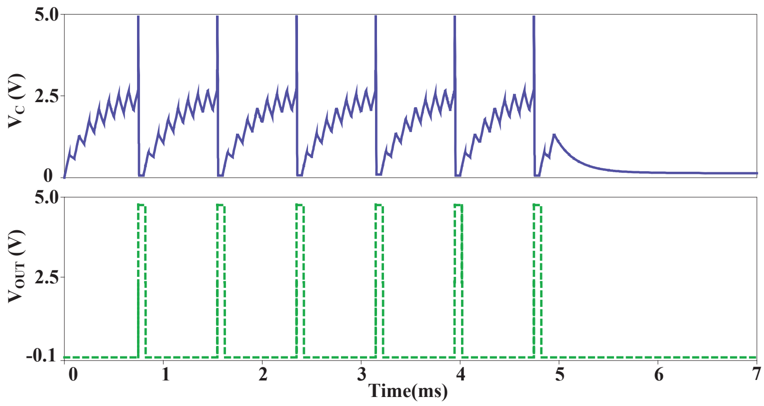

Fig. 5: The simulation of the neuron model. V_C is the voltage on the membrane capacitors C_1 and C_2 in Fig. 4. V_{OUT} represents the voltage pulse output by the neuron in the 'OUT' terminal in Fig. 4.

In the PSPICE simulation, the PMOS transistors T_{n1}, T_{n2} and T_{n4} are based on the M2SJ136 model, and the threshold voltage is about $-2.0V$. The NMOS transistors T_{n3}, T_{n5}, T_{n6} and T_{n7} are based on the M2SK530 model, where the corresponding threshold voltage is about $2.1V$. The membrane capacitors C_1 and C_2 are set to $10uF$, and their capacitance can be adjusted appropriately to control the firing frequency of neurons. Besides, we set $R_1 = 2(k\Omega)$, $R_2 = 2(k\Omega)$ and $C_3 = 0.2(uF)$ in this simulation. By adjusting the resistance R_2 and the capacitance C_3 of the differential monostable trigger, it is flexible to change the output pulses' width of the neuron.

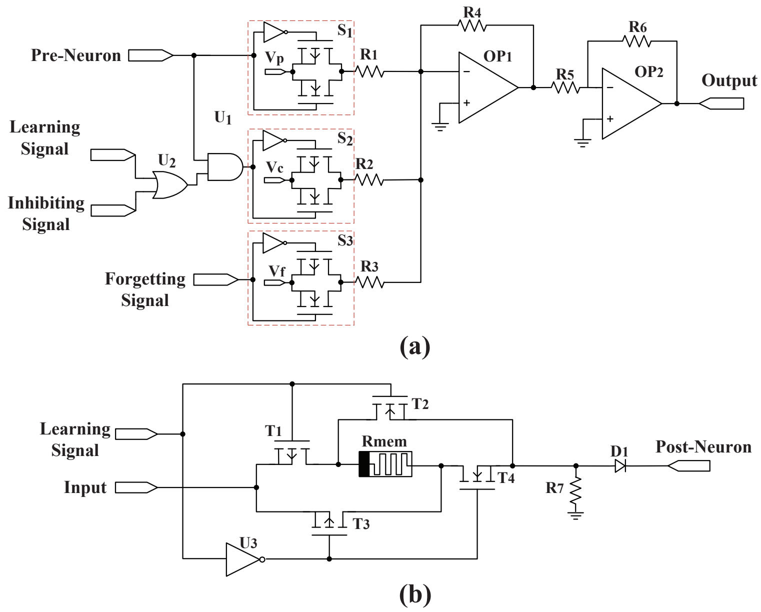

Fig. 6: The circuit of the synapse model. (a) The Control Signal Module. (b) The Weight Adjustment Module.

4.3 Synapse module

Synapses are key bonds which connect pre-neurons and post-neurons. By adjusting the synaptic weights, the association between the pre-neurons and the post-neurons is strengthened or weakened. Memristor plays a key role in realizing the synaptic function in this paper, which dynamically strengthens or weakens the synaptic strength between neurons by adjusting the memristance. For the convenience of description, the synapse module is explained in two parts, the first part is the Control Signal Module and the second part is the Weight Adjustment Module. The circuit design of the entire synapse is shown in Fig. 6. In this paper, the operational amplifiers in the synapse module are all based on the TL082 type for simulation, where the power supplies are set as $+15V$ and $-15V$. The value of $R_1 - R_6$ are set $1k\Omega$ to assist the amplifiers to complete the sum operation and inversion operation. R_7 is initialized to 500Ω, it is a threshold resistor to set the thresholds of the synaptic weight and its detailed settings are described in the next section.

The Control Signal Module is designed to receive control signals, which is presented in Fig. 6(a). Amplifier OP_1 is a summing operational amplifier while OP_2 is an inverting operational amplifier. The Pre-neuron signal is the output signal from the pre-neuron. When the pre-neuron is at active state, the switch S_1 will be turned on and the high-level voltage V_p will be applied to the Weight Adjustment Module. The learning signal is used to establish associative memory in the learning stage. Specifically, when the learning signal and the input signal of pre-neuron are generated at a certain time synchronously, the switches S_1 and S_2 will be turned on and the sum of voltages V_p and V_c will be applied to strengthen the synaptic strength. When the inhabiting signal is generated in the gradual transferring stage, the switches S_1 and S_2 will also be turned on but the sum of voltages V_p and V_c will be applied to weaken the connection strength between the pre-neurons and post-neurons. The forgetting stage can be explained as a reverse process of the learning stage. In the forgetting stage, there are neither learning signal nor inhibiting signal. Only the switch S_3 will be turned on and the voltage V_f will be applied to weaken the synaptic strength.

In Fig. 6(b), the Weight Adjustment Module is presented. The transistors T_1, T_2, T_3 and T_4 are controlled by the learning signal, which aim to determine the direction of input current flowing through the memristor *Rmem*. Specifically, when the learning signal is at high level, the transistors T_2 and T_3 will be turned on while T_1 and T_4 will be turned off. The input current flows from the input terminal through T_3, *Rmem* and T_2 to post-neuron. When the learning signal is at low level, the transistors T_1 and T_4 will be turned on while T_2 and T_3 be turned off and the current will flow from T_1, through *Rmem* and T_4 to the post-neuron terminal. The role of the diode D_1 is to prevent the reverse current flowing from the post-neuron terminal.

4.4 Repeatable Monostable Trigger

Most rules of associative memory neural networks demand that the signals are generated synchronously to establish associative memory. However, it is difficult to control the spikes output by neurons to be synchronous due to the different initial parameters and initial state of the leaky integrate-and-fire neuron, which means time delay will occur. This may require strictly setting the parameters of the pre-neuron and the post-neuron to be consistent. Nevertheless, if the input signals do not appear at the same time, the output spikes of the neurons will be also asynchronous. For example, as shown in Fig 7, the voltage V_{in1} is the input signal of *Neuron 1* while V_{in2} is the input signal of *Neuron 2*, the parameters of *Neuron 1* and *Neuron 2* are set to be exactly same. It is worth noting that the frequencies and amplitudes of V_{in1} and V_{in2} are identical, but V_{in2} is applied earlier than V_{in1}. As a result, the output spikes of *Neuron 1* and *Neuron 2* are not synchronized.

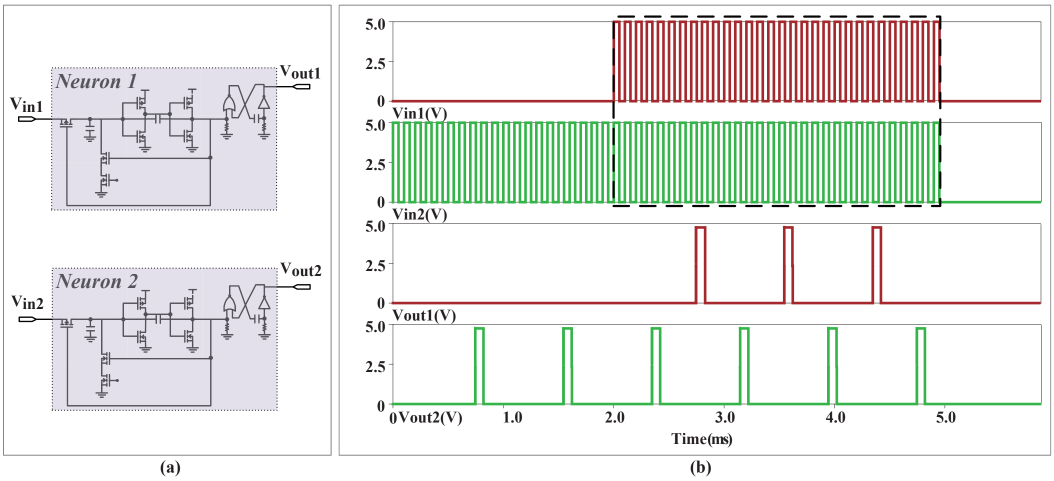

Fig. 7: Simulation of the signals "asynchronous" problem between neurons. (a) The connection diagram of *Neuron 1* and *Neuron 2*. (b) The input and output signals of *Neuron 1* and *Neuron 2*. V_{in1} and V_{in2} are the input voltages of *Neuron 1* and *Neuron 2* respectively. V_{out1} and V_{out2} are the output of *Neuron 1* and *Neuron 2* respectively. The parameters of *Neuron 1* and *Neuron 2* are set to be the same as the parameters in Fig. 4. If the input voltage V_{in1} is applied earlier or later than V_{in2}, the output pulses of *Neuron 1* and *Neuron 2* will be asynchronous.

Considering the issues of time delay and asynchronism between the output spikes of neurons, the repeatable monostable trigger is used to establish associative memory. The repeatable monostable trigger used in this paper is proposed in the paper [7], which is simplified from the integrated repeatable monostable trigger MC14528. The circuit schematic is shown in Fig. 8.

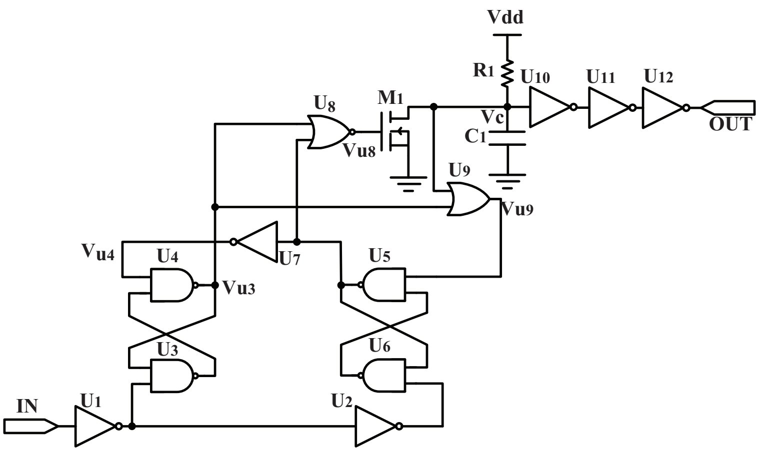

Fig. 8: The circuit schematic of the repeatable monostable trigger.

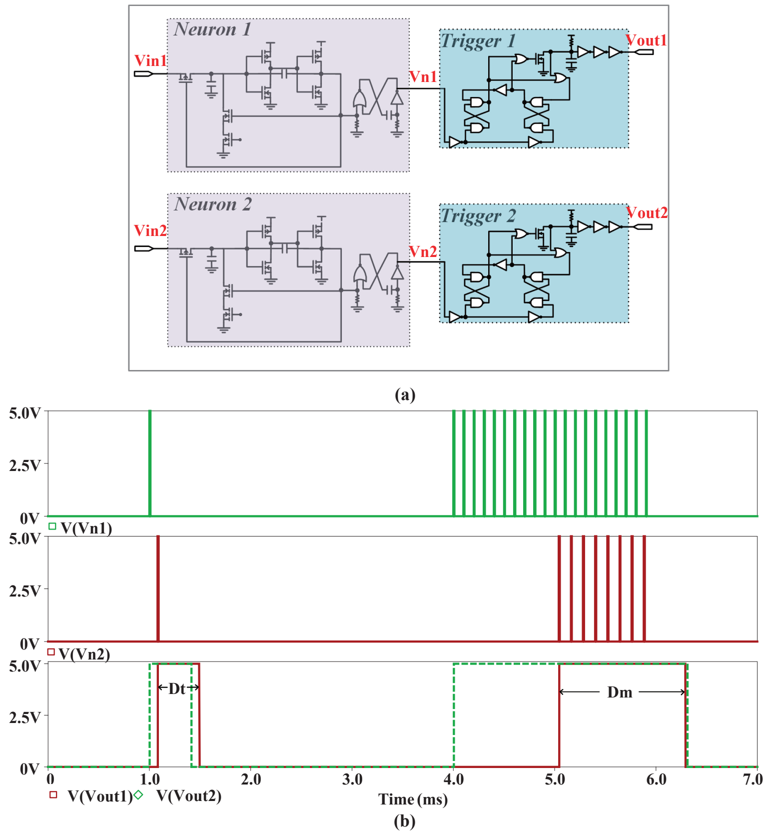

Fig. 9: The simulation of the repeatable monostable trigger. (a) Connected circuit diagram between neurons and triggers. (b) The simulation results. V_{n1} and V_{n2} are the output signals of *Neuron 1* and *Neuron 2* respectively. Meanwhile, V_{n1} and V_{n2} are used as the input signals of *Trigger 1* and *Trigger 2*. V_{out1} and V_{out2} are the output signals of *Trigger 1* and *Trigger 2*, respectively.

In the initial state, the voltage $V_{u3} = 1$, $V_{u8} = 0$ and the circuit is at steady state. The transistor M_1 is turned off while the capacitor C_1 is charged by the voltage V_{dd}. If there are no positive voltage signals entering, the circuit will keep at a steady state. When a positive pulse enters the IN terminal of the trigger, V_{u3} and V_{u8} will turn to 0 and 1 respectively, then the transistor M_1 will be turned on and the capacitor C_1 will discharge via the transistor M_1. As a result, the voltage V_c will decrease gradually. When V_c drops below the threshold voltage V_{th10} of the NOT gate U_{10}, the circuit enters a transient steady state, but this state cannot be always maintained and the voltage V_c continues to decrease. When V_c drops below the threshold voltage V_{th9} of the U_9, $V_{u9} = 0$ and $V_{u3} = 1$. Meanwhile, the transistor M_1 is turned off again and C_1 begins to recharge. Finally, the circuit will return to the steady state when the voltage V_c exceeds the threshold of U_{10} again. The function of U_{11} and U_{12} is to shape the signal output by U_{10} terminal, which makes the final output waveform of the trigger closer to the rectangle wave. According to the above analysis, the capacitor C_1 will recharge and the voltage V_c will rise after the circuit experiences the transient steady state. Especially, while V_c is rising from V_{th9} to V_{th10} and another positive signal triggers the circuit,$V_{u3} = 0$, $V_{u8} = 1$. Then, the transistor M_1 will turn on and the capacitor C_1 will discharge again, which means the circuit returns to the transient steady state. The trigger will not return to the steady state until the capacitor C_1 keeps charging to the condition $Vc > V_{th10}$ and there are no trigger signals applied to the IN terminal in certain time interval.

The simulation of the repeatable monostable trigger is shown in Fig. 9. The voltage V_{n1} and V_{n2} are output signals of *Neuron 1* and *Neuron 2*, as well as the input signals of *Trigger 1* and *Trigger 2*. V_{out1} and V_{out2} are the corresponding output signals of *Trigger 1* and *Trigger 2*, respectively. When a high-level voltage signal enters the trigger, the duration of this signal will be last for a period of time D_t. In this duration, if there are other input signals that continue to trigger the trigger, the lasting time will be extended to D_m as indicated in Fig. 9. Therefore, the trigger will be able to judge the neuron whether at firing state while there are continuous output spikes in the neuron. When two or more neurons are at firing state and the firing time intervals do not exceed the maximum lasting time D_t of the trigger, although the frequencies of the spikes are different and the spikes appear asynchronously, associative memory can be established conveniently.

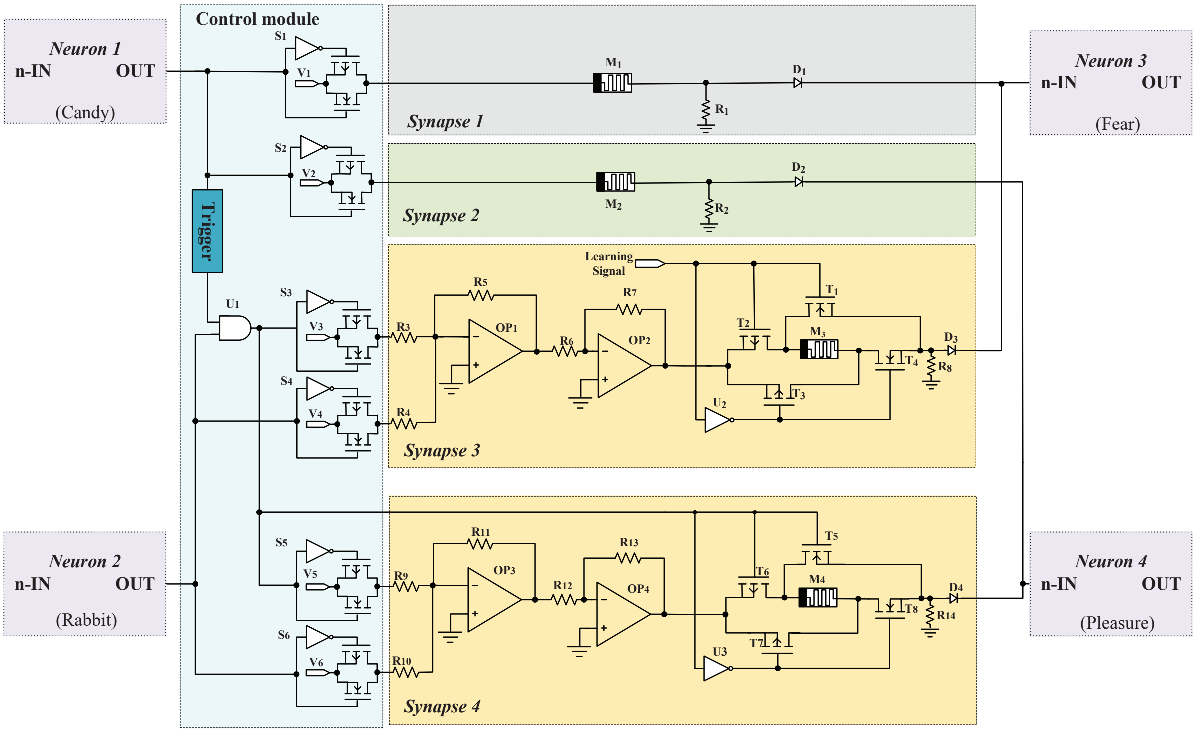

Fig. 10: The circuit design of the gradual transferring stage based on "The Case of Peter" experiment.

5 Circuit Design of Emotional Gradual Transfer Process

5.1 Circuit Analysis

The circuit design of "The Case of Peter" for showing the emotional gradual transfer process is presented in Fig. 10.

Neuron 1 represents a taste receiver, which is renamed as the candy neuron in the circuit design for convenience. It can receive the taste signal of tasting candy. *Neuron 2* represents a visual receiver and can receive the visual signal of seeing the rabbit, which is named as the rabbit neuron similarly. When *Neuron 1* and *Neuron 2* receive the taste signal from the candy and the visual signal from the rabbit, and these signals make the voltages of the membrane capacitors exceed the threshold voltages of the two neurons, the two neurons will be activated and at the excited state. *Neuron 3* and *Neuron 4* are both emotional expression neurons and can be named as the fear neuron and the pleasure neuron, respectively. The connected synapse between the candy neuron and the fear neuron is *Synapse 1*. And *Synapse 2* connects the candy neuron and the pleasure neuron. As "The Case of Peter" described as above, Peter felt pleasure once he received candy because the candy is an unconditioned stimulus, which means the synaptic strength between the candy neuron and the pleasure neuron is strong. Meanwhile, the synaptic strength between the candy neuron and the fear neuron is weak. Therefore, the weights of *Synapse 1* and *Synapse 2* are set to a high value and a low value, respectively, and they will not change during the experiment. *Synapse 3* connects the rabbit neuron and the fear neuron while *Synapse 4* connects the rabbit neuron and the pleasure neuron. Since the rabbit is a conditioned stimulus, the synaptic strength of *Synapse 3* and *Synapse 4* will change during the experiment. The weights of *Synapse 3* and *Synapse 4* are set to a high value and a low value before the experiment, respectively, which represents the connection strength between the *Neuron 2* and *Neuron 3* is strong while the synaptic strength between the *Neuron 2* and *Neuron 4* is weak at the beginning. In this paper, the synaptic weight is defined as following:

$$W = \frac{R_{off} - R_m}{R_{off} - R_{on}} \tag{6}$$

where R_m is the memristance, R_{off} and R_{on} are the maximum resistance and minimum resistance of memristor respectively.

In Fig. 10, the Trigger is the repeatable monostable trigger mentioned in Section 3. The control module is utilized to judge the stage of the circuit. The resistors R_1, R_2, R_8 and R_{14} aim to adjust the weight thresholds of *Synapse 1*, *Synapse 2*, *Synapse 3* and *Synapse 4*, respectively. When the input voltage of the n-IN terminal is less than the threshold V_{th} of these neurons, there will be no spikes output from their OUT terminal, in other words, these neurons will be at an inactive state. Therefore, in order to trigger the neuron, the input voltage must exceed the threshold V_{th}. For example, if there is rabbit signal alone, in order to trigger the pleasure neuron, the following condition must be satisfied ignoring the effects of parasitic capacitance, resistance, and inductance of transistors:

$$\frac{V_5 + V_6}{R_{M4} + R_{14}} \times R_{14} > V_{th} + V_{d4} \tag{7}$$

where V_{d4} is the forward voltage drop of the diode D_4. R_{M4} is the memristance of the memristor M_4. From the formulas (6) and (7), the condition is rewritten as:

$$W_4 > \frac{(R_{14} + R_{off})(V_{th} + V_{d1}) - (V_5 + V_6)R_{14}}{(V_{th} + V_{d4})(R_{off} - R_{on})} \tag{8}$$

Therefore, the weight threshold W_{th4} of *Synapse 4* is derived as:

$$W_{th4} = \frac{(R_{14} + R_{off})(V_{th} + V_{d1}) - (V_5 + V_6)R_{14}}{(V_{th} + V_{d4})(R_{off} - R_{on})} \tag{9}$$

According to the formula (9), the synaptic weight can be adjusted by the resistor R_{14}. The other three thresholds of synaptic weight W_{th1}, W_{th2} and W_{th3} can be calculated in the same way. Thereby, when the synaptic weight W_4 exceeds the threshold W_{th4}, *Neuron 2* can trigger *Neuron 4* alone.

Because the experiment does not involve the natural forgetting process, the forgetting state is not shown in the circuit, which will be presented in the next section.

5.2 Simulation Results of The Circuit

The simulation result completed by PSPICE is presented in Fig. 11. $V(N_1)$, $V(N_2)$, $V(N_3)$ and $V(N_4)$ are the output spikes from *Neuron 1*, *Neuron 2*, *Neuron 3* and *Neuron 4*, respectively.

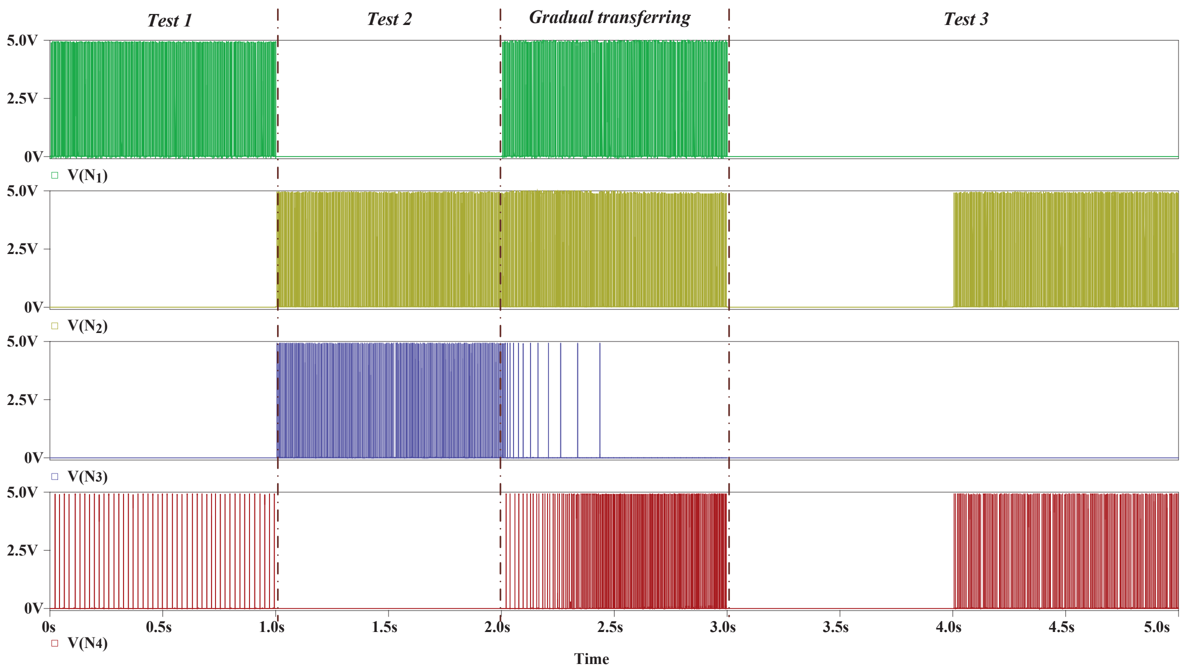

Fig. 11: The simulation results of “The Case of Peter” experiment for showing the gradual transferring stage.

In *Test 1*, there is only the candy signal that triggers the candy neuron. When the high-level pulses are output from the candy neuron, the switches S_1 and S_2 will turn on and the voltages V_1 and V_2 are applied to the *Synapse 1* and *Synapse 2*, respectively. Because the memristance of M_1 is set very high and then the synaptic weight is lower than the threshold W_{th1} of *Synapse 1*, the fear neuron cannot be triggered, which means the fear feeling is not produced. On the contrary, the memristance of M_2 is set very low and then the synaptic weight is higer than the threshold W_{th2} of *Synapse 2*, the pleasure neuron is triggered and the feeling of pleasure is produced.

In *Test 2*, only the pre-neuron *Neuron 2* is triggered by the rabbit signal and the *Neuron 1* is at an inactive state. Thus, when the spikes are output from *Neuron 2*, the AND gate U_1 is closed, only the switches S_4 and S_5 will turn on and the voltages V_4 and V_6 will be apply to the *Synapse 3* and *Synapse 4*, respectively. Because of the strong strength of *Synapse 3* and the weak strength of *Synapse 4* at first, the fear neuron is triggered by *Neuron 2* alone but the pleasure neuron not. Meanwhile, the learning signals of *Synapse 3* and *Synapse 4* are at a low level, V_4 and V_6 are lower than the threshold voltages of the memristors M_3 and M_4. Therefore, the memristance of M_3 and M_4 will not change while the synaptic weight of *Synapse 3* and *Synapse 4* remains unchanged.

In the *Gradual transferring* stage, both the candy neuron and the rabbit neuron are at excited state, which means Peter received the candy signal and the rabbit signal almost simultaneously. The repeatable monostable trigger is triggered at this stage and then the gate U_1 is opened. Meanwhile, The switches $S_1 - S_6$ are turned on, the voltages V_1 and V_2 are applied to *Synapse 1* and *Synapse 2*, respectively. The sum of V_3 and V_4 , which is higher than the absolute value of the voltage threshold of memristor M_3 ($V_3 + V_4 > |V_{T-}|$) is applied to *Synapse 3*. Because there is no unconditional stimulus related to fear feeling, the learning signal is at low level and the transistors T_2, T_4 are turned on while T_1 and T_3 are turned off. As a result, the memristance of M_3 increases, which means the synaptic strength is weakened gradually. Meanwhile, the voltages V_5 and V_6 ($V_5 + V_6 > |V_{T+}|$) are applied to the *Synapse 4* and the transistors T_2, T_4 are turned off while T_1 and T_3 are turned on. As a result, the memristance of M_4 decreases and then the synaptic strength is strengthened gradually. The change process of synaptic weight is shown in Fig. 12. At first, the rabbit neuron can trigger the fear neuron alone. As the weight of *Synapse 3* decreases, the firing frequency of the fear neuron continues to decrease. When the synaptic weight of *Synapse 3* drops down below the threshold W_{th3}, the rabbit neuron loses the ability to trigger the fear neuron alone and the fear neuron stops to fire, which means the feeling of fear is gradually weakened and disappears at last. At the same time, when the synaptic weight of *Synapse 4* exceeds the threshold W_{th4} as the weight of *Synapse 4* increases, the rabbit neuron can trigger the pleasure neuron alone and the firing frequency of the pleasure neuron increases gradually. The excitement of pleasure neurons is gradually strengthened, and the excitement of fear neurons is gradually weakened or even suppressed. As a result, the pleasure feeling is gradually strengthened. The *Gradual transferring* stage is completed, the pleasure feeling replaced the fear feeling and became the core emotion.

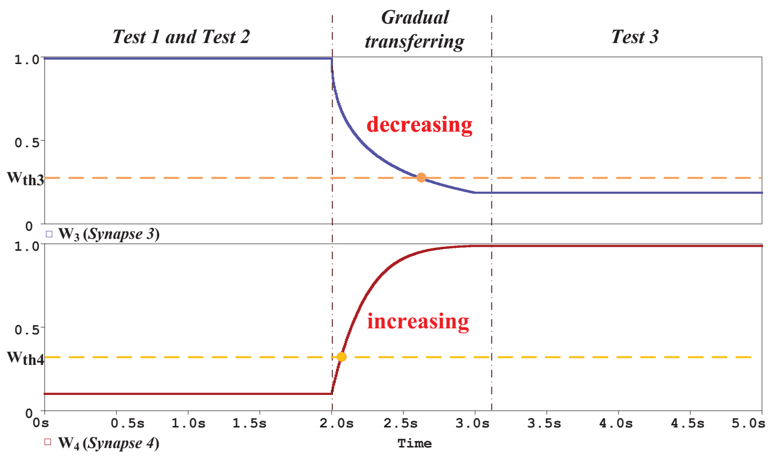

Fig. 12: The change of the synaptic weights W_3 and W_4. In the gradual transferring stage, the synaptic weight W_3 is deceasing while the synaptic weight W_4 is increasing.

The *Test 3* stage is to judge whether the *Gradual transferring* stage is completed. As Fig. 11 shows, when only the rabbit neuron fires, the pleasure neuron, instead of the fear neuron, is triggered. In other words, the fear feeling disappears and the pleasure feeling is produced.

6 Affective Associative Memory Neural Network with Gradual Processes

6.1 Circuit Design

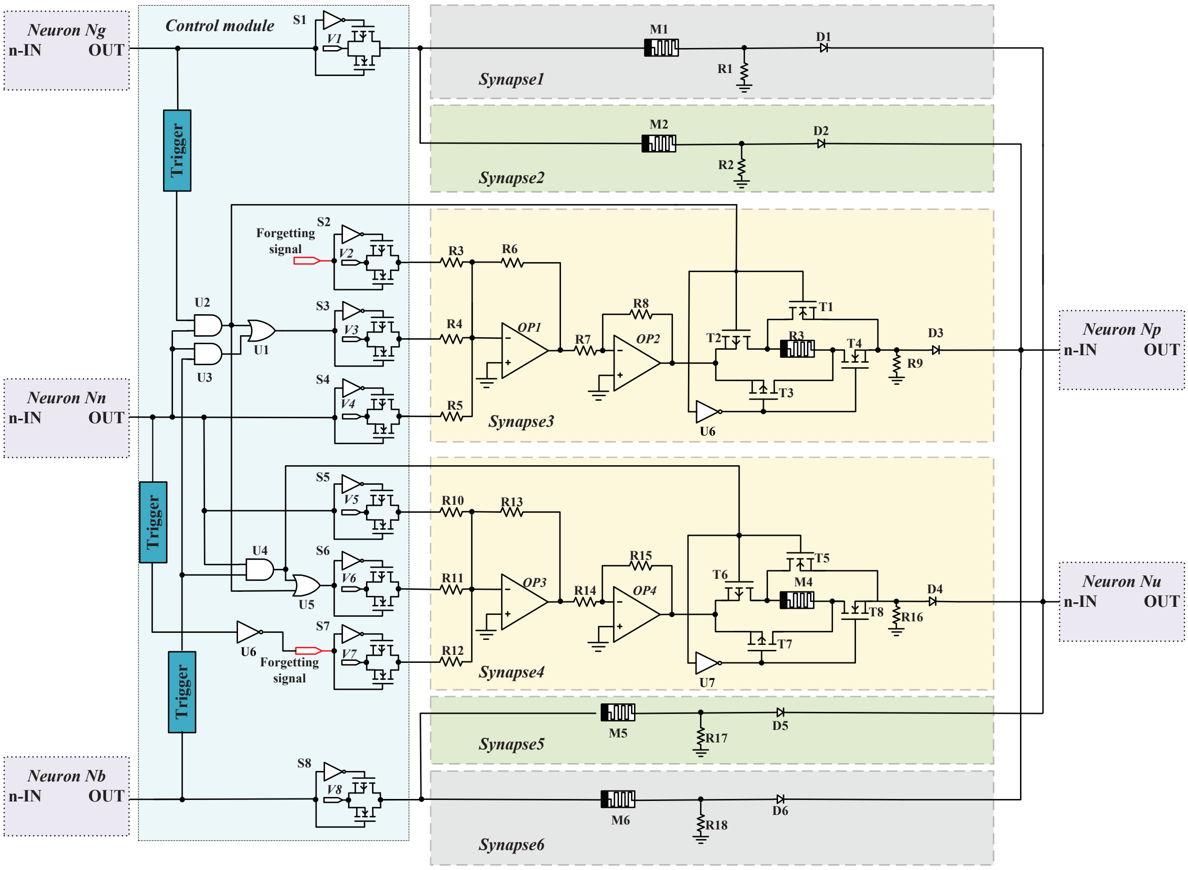

Fig. 13: The circuit design of affective associative memory neural network with the functions of gradual learning, gradual transferring and gradual forgetting.

Emotions are important psychological and physical phenomena. In daily life, people will show pleasure expression about good news and upset expression about bad news, which can be defined as the unconditioned responses in the associative memory theory. The good (bad) news is the unconditioned stimulus of pleasure (upset) emotion. If there is a news notification signal which represents the neutral stimulus, people will show no emotions at first. When the news notification always follows good news, people will show pleasure and the pleasure emotion will gradually rise until becoming stable. After that, though only the notification of news is coming without the content of news, people will also show pleasure. Same as above, when the notification is always followed by bad news, people will also show upset without the content of news after the notification coming. As a result, the news notification gradually turns to be the conditioned stimulus. This is the gradual learning stage in the process of affective associative memory. Besides, if the notification is re-associated with the bad news (good news) after it has been associated with the good news (bad news), the pleasure (upset) emotion will decline gradually and the upset (pleasure) emotion will rise gradually. This is the gradual transferring stage. If there is no news notification for a long time, the association between the news notification and good or bad news will gradually be weakened until it disappears, which is called the forgetting stage.

The circuit of the affective associative memory neural network is shown in Fig. 13. The neural network has three input neurons and two output neurons. Specifically, as shown in Fig. 13, the neurons Ng, Nn and Nb are the input neurons while Np and Nu are the output neurons. Besides, the neurons Ng, Nn and Nb receive the signals of good news, notification and bad news, respectively. When received the corresponding signal, the neurons will be activated and output spikes. The neurons Np and Nu are emotion expression neurons. When the feeling of pleasure (upset) is produced, the Np (Nu) neuron will be activated. The *Synapse 1-Synapse 6* connect the pre-neurons and post-neurons. The appearance of good news will not

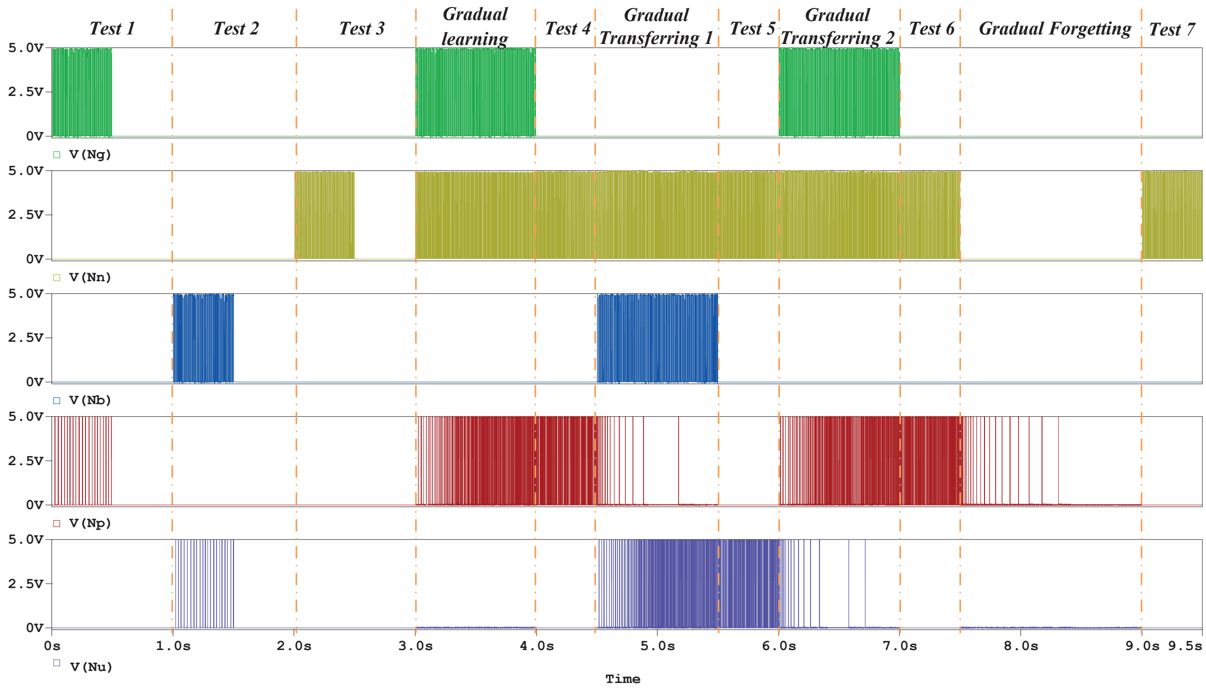

Fig. 14: PSPICE simulation result of the affective associative memory neural network with the gradual learning, gradual transferring and gradual forgetting stages

cause the upset emotion, so the synaptic strength of *Synapse 1* is weak and the synaptic weight W_{S1} is less than the threshold W_{th1} of *Synapse 1*. For the same reason, the synaptic weight W_{S6} is less than the threshold W_{th6}. Similarly, the good news will always cause the pleasure emotion while the bad news will cause the upset emotion, thus the synaptic weight W_{S2} and W_{S5} are set as a constant value higher than the thresholds W_{th2} and W_{th5} of *Synapse 2* and *Synapse 5*, respectively. The weight of *Synapse 3* and *Synapse 4* will be strengthened or weakened in the stage of gradual learning, gradual transferring or gradual forgetting. The change of weight ΔW can be calculated as follows.

$$\Delta W^t = \Delta W^t_{learn} - \Delta W^t_{tran} - \Delta W^t_{forg} \tag{10}$$

where ΔW^t_{learn}, ΔW^t_{tran}, ΔW^t_{forg} are the changed weight in the gradual learning, gradual transferring and gradual forgetting stage respectively. Specifically, for the *Synapse 4*, the rules for calculating ΔW^t_{learn}, ΔW^t_{tran}, ΔW^t_{forg} are listed as the following equations.

$$\begin{cases} \Delta W^t_{learn} = \Delta\omega_l \times sgn(Nb)sgn(Nn) \\ \Delta W^t_{tran} = \Delta\omega_t \times sgn(Ng)sgn(Nn) \\ \Delta W^t_{forg} = \Delta\omega_f \times [1 - sgn(Nn)] \end{cases} \tag{11}$$

where $\Delta\omega_l$ is the change of W_{S4} in the gradual learning stage and $\Delta\omega_t$ is the change of W_{S4} in the gradual transferring stage and $\Delta\omega_f$ is the change of W_{S4} in the gradual forgetting stage. The sgn is a function defined as

$$sgn(Nx) = \begin{cases} 1 & Nx \text{ is activated} \\ 0 & Nx \text{ is not activated} \end{cases} \tag{12}$$

where Nx represents the neurons Ng, Nn or Nb. The synaptic weight change rule for *Synapse 3* can be derived in the same way as for *Synapse 4*. At the learning stage, the memristance (M_3 or M_4) will decrease, which leads to the increase of the synaptic weight. If the circuit is at the gradual forgetting stage, the memristance will increase and the synaptic weight will decrease. In the gradual transferring stage, the increase or decrease of the synapse weights are determined by the input neurons and the control module. However, before the learning stage, the synaptic weights of *Synapse 3* and *Synapse 4* are less than the synaptic thresholds, thus the neurons Np and Nu will not be activated by firing the Nn neuron alone.

The control module is utilized to judge the state of the affective associative memory neural network. The Trigger is used to solve the problems of time delay and asynchronism between the output spikes of neurons.

6.2 Simulation and analysis

The simulation result of the affective associative memory neural network is shown in Fig. 14. The test stages aim to test the current emotional state. In *Test 1*, there is only good news signal, the Ng neuron will be activated and output spikes. Because of the strong weight between neurons Ng and Np, Np will be triggered, which means the pleasure feeling is produced. On the contrary, the synaptic weight between neurons Ng and Nu is weak, Nu will not respond and there is no upset feeling. In *Test 2*, there is only bad news and the neuron Nb is activated , the neuron Nu will be activated while the neuron Np will not respond.

In the *Gradual learning* stage, both the good news signal and the notification signal are input to the neurons Ng and Nn, Ng and Nn are triggered together. At this time, the learning signal of *Synapse 3* is at high level and the transistors T_1 and T_3 will be turned on while T_2 and T_4 will be turned off, the sum of voltages V_3 and V_4 will be applied to *Synapse 3*. The current flows through T_3, M_3 and T_1 to the neuron Np, which causes the memristance of M_3 decreasing and the synaptic weight of *Synapse 3* increasing. As a result, the firing frequency of the neuron Np gradually increases, which means the feeling of pleasure is stronger and stronger gradually when the notification comes. This is the learning process with gradually increasing emotional intensity. The purpose of *Test 4* is to verify whether the learning process has been completed.

In the *Gradual Transferring 1* stage, the neurons Nn and Nb send out spikes together, before the forgetting stage, the association between the notification and good news has not been forgotten. Due to the strong strength of *Synapse 3* and *Synapse 4* at this time, the neurons Np and Nu are all activated, which means the complex emotion is generated. The voltages V_3, V_4 are applied to the *Synapse 3* while V_5, V_6 are applied to *Synapse 4*. While the learning signal of *Synapse 3* is at low level state, the transistors T_2, T_4 are turned on and T_1, T_3 are turned off. The current flows through T_2, M_3 and T_4 to the Np neuron, which causes the decreases of the synaptic weight of *Synapse 3*. Therefore, the firing frequency of the neuron Np decreases, which means the feeling of pleasure becomes weaker gradually. Meanwhile, the current flows through T_7, M_4 and T_5 causing the increase of the firing frequency of the neuron Nu. As a result, the neuron Np is inhibited and the firing frequency of Nu exceeds the peak. The *Test 5* is to verify the gradual transferring result in the *Gradual Transferring 1* stage. From the *Test 5*, the feeling of pleasure is weakened and disappears while the feeling of the upset is strengthened in the process.

In the *Gradual Transferring 2* stage, the neurons Nn and Nb send out spikes together. After the *Gradual Transferring 1* stage, the feeling of fear has not been forgotten. Therefore, the mixed complex emotions are generated again. In contrast with the *Gradual Transferring 1* stage, the synaptic weight W_{S3} of *Synapse 3* increases gradually while the synaptic weight W_{S4} of *Synapse 4* decreases gradually. Therefore, the firing frequency of the neuron Np increases and the feeling of pleasure gradually becomes stronger. Meanwhile, the feeling of upset is weaker and weaker with the decreasing firing frequency of the neuron Nu. In *Test 6*, there is only a notification signal, the feeling of pleasure is generated and the upset feeling has disappeared, which means the pleasure feeling has become the core emotion and replaced the fear feeling.

In the *Gradual Forgetting* stage, there are no notification signals input to the Nn neuron, so the forgetting process takes place. In this stage, the forgetting signals of *Synapse 3* and *Synapse 4* are at high-level states and the switches S_2 and S_5 are turned on, the voltages V_2 and V_7 are applied to *Synapse 3* and *Synapse 4* to make the memristors M_3 and M_4 return to a high-impedance state gradually. Therefore, the synaptic weights of *Synapse 3* and *Synapse 4* are weaker and weaker, which means the association between the neurons Nn and Ng or the neurons Nn and Nb is forgotten. As a result, the firing frequencies of the emotional expression neurons will decrease and the generated emotions will become weaker gradually and disappear at last. In *Test 7*, it is verified that no emotions will be generated when the notification appears, which means the forgetting process is completed.

7 Conclusion

The affective associative memory neural network has been studied in recent years. In the existing memristor-based affective associative memory model, the change of emotions in learning and forgetting processes is abrupt and the intensity of emotions is invariable. Further, the gradual processes in learning, forgetting and transferring stages are not considered. In this work, a memristor-based affective associative neural network has been proposed, which includes the gradual learning, gradual forgetting and gradual transferring functions with variable emotional intensity. In the designed circuit, the memristors are utilized to define the synaptic weights. When the memristance decreases, the corresponding synaptic weight will increase and the synapse strength will be stronger. Making use of the leaky integrate-and-fire neuron model, the firing frequency of the output neurons is variable. By correlating the emotional intensity with the firing frequency of output neurons, the intensity of emotions can gradually change from strong to weak or from weak to strong, which is in line with the changing laws of human emotions. Compared with the existing affective associative memory neural network model, the circuit proposed in this paper can better imitates the changing process of human emotions, which provides new ideas for modeling the intelligent functions of the human brain and realizing emotional robots. Future works will focus on the design of more compact circuit and more efficient practical applications based on affective associative memory neural network.

Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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